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Triple Threat Gateway? Respiratory Health, Demographics and Land Use in Metro East St. Louis, Missouri-Illinois, USA

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Abstract

This paper examines a triple threat for residents of two counties in the St. Louis metropolitan area. Previous environmental justice research has focused on demographics and toxic facilities. This research builds upon those assessments by incorporating hospital discharge data and demographics as well as three different types of pollution sources. Air pollution monitors were unavailable to use during the time period of 2009-2011, therefore proxy measures of pollution in the form of major roadways, industrial land use parcels, and toxic facility information from the EPA Toxic Release Inventory are utilized. This study integrates both spatial coincidence and proximity analysis methods and geostatistical techniques to account for spatial autocorrelation present in the data. Findings indicate that there is not a triple threat occurring, but rather a double burden with residents in poverty having higher risk for respiratory hospitalizations.

Keywords

Medical Geography, Environmental Justice, Pollution, Respiratory Health, Spatial statistics, GIS

Acknowledgements

Financial support was provided by SIUE Research and Equipment Tools Grant to purchase the discharge data from the Illinois Department of Public Health. I also wish to thank the Missouri Department of Health and Human Services for providing discharge data for Illinois residents that use Missouri Hospitals. I also appreciate the help from the GIS departments in Madison and St. Clair County governments. I would also like to thank the reviewers for their insightful and useful suggestions.

1 INTRODUCTION

Exposure to air pollution increases human health risks (Brender et al. 2011; Brunekreef and Holgate 2002). Unfortunately, many researchers have found that the health risks of exposure to air toxins are disproportionately affecting minorities and low-income residents (Gilbert and Chakraborty 2011; Maantay 2007). Crouse et al. (2009) identified a double burden for those urban areas with high levels of deprivation and high levels of ambient air pollution. In particular response to respiratory problems, exposure to major air pollutants, such as ozone and particulate matter have been found to contribute to overall mortality and morbidity levels, as well as asthma and lung cancer (James et al. 2012; Maantay 2007). Different segments of the population have varying levels of exposures and therefore, varying levels of health risk (James et al. 2012). This study will examine population and potential health risks of the built environment in regard to respiratory hospitalizations at the zip code level in two counties of the St. Louis MO-IL Metropolitan Statistical Area (MSA), which is colloquially known as the Metro East. These community factors include three environmental exposures: point sources of pollution consisting of the United States Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI) facilities, roadways which account for a large proportion of pollution in our advanced post-industrial society, and industrial land use parcels. Geographic Information Systems (GIS) will be used to analyze the spatial relationship between areas of respiratory hospitalizations, demographics and sources of air pollution. The purpose of this study is to determine if there is a spatial link between known respiratory disease-causing pollutants, demographics, and areas of respiratory hospitalization in the Metro East. This study aims to identify a potential *triple threat* by analyzing the association between various air pollution sources, demographics, and respiratory health. This research stems from the call to make a systematic connection between air pollution and health by focusing on varying types of air pollution instead of relying only on point source pollution (Gilbert and Chakroborty 2011, 274).

There have been three studies that have researched St. Louis air quality (Abel 2008; Sarnat et al. 2015; Winquist et al. 2012). Abel chose an environmental justice approach to analyze pollution emitting factories as well as exposure risk for the St. Louis MSA. Using conventional proximity analysis, minority and low-income residents lived closer to sources of industrial pollution. However, when analyzing the exposure risk to pollution, a much more concentrated geographic area was found that resulted in high minority, low-income residents exposed to the most hazardous facilities in the whole MSA. Winquist et al. found an additional association between asthma and ozone and congestive heart failure and ozone. Winquist et al. analyzed six years of hospitalization data and two monitoring sites in St. Louis. Rather than only focusing on disease type and pollution, their study also analyzed where people tended to get care. Older adults with more severe diseases tended to be admitted to a hospital, whereas the poor and the younger populations tended to only utilize the emergency room. Finally, taking a more detailed analysis into one specific type of pollutant, particulate matter, Sarnat et al. found a strong association between cardiorespiratory emergency department visits and particulate matter. Only one monitoring station was used, but it collected 24 different pollutants over the span of twenty-three months. Various pollutants impacted hospitalizations differently. For example, ozone was found to have an association with respiratory disease, whereas cardiovascular disease was more susceptible to $PM_{2.5}$ components. Sarnat et al's study found positive associations with various pollutants and cardiorespiratory morbidity in the St. Louis area. This article will build upon these previous studies by incorporating a geographic and spatial perspective with the built environment and health outcomes. Although no specific pollutants will be examined, the location of multiple pollution sources are mapped and analyzed as well as the geographic distribution of respiratory hospitalizations and demographics.

2 DATA AND METHODS

2.1 Study Area

The Metro East is home to over 500,000 people spread across two counties in Illinois covering 1,415 square miles. It is part of the St. Louis MSA and is home to multiple universities, retail, industrial areas such as a steel mill and coke plant, a UNESCO World Heritage Site, Cahokia Mounds, as well Scott Air Force Base. This area also grows many crops such as corn, soybeans, and horseradish. The St. Louis MSA has a long industrial history and is known as a major industrial and transportation hub with multiple break-in-bulk options. St. Louis is still a major beer and whiskey producer along with oil refineries, steel mills, and chemical companies (Abel 2008). The study area has a significant population gradient with most of the population residing on the western edge, while on the eastern edge, there is less population and more agricultural production. This gradient can be seen when looking at population density (Figure 1) along with other maps throughout this article.

Air quality in St. Louis follows an inconsistent pattern. "Over 300 industrial facilities find their home in this region and St. Louis has some of the highest concentrations in the country of ozone, lead, and cadmium" (Abel 2008, 236). In 1991, the region was in non-attainment for one-hour ozone in 1979, but in 2002 the region was in attainment. However, in July 2012, the region was designated as marginal non-attainment for 2008 one-hour ozone, but in February 2015, attainment was reached for the 1997 eight-hour ozone standard. A similar inconsistent pattern exists for particulate matter. In 2005, the region was in non-attainment for the 1997 $PM_{2.5}$ standard, yet in 2009, attainment was achieved. Currently, the region is deemed 'unclassified' for 2012 due to data monitoring issues (East-West Gateway 2015). The EPA ranked Madison County with the second highest cancer risk in the country due to air pollution, second only to Los Angeles County, California in 2009.

2.2 Health, Demographic and Environmental datasets

Three data sets are needed in this analysis: respiratory hospitalizations, demographic data, and location information on pollution sources. The location of pollution sources is used due to the lack of monitoring stations of specific pollutants in the region. While most pollutants travel away from the point source, the locations are used in this study as a way to circumvent the lack of specific pollution data in the region.

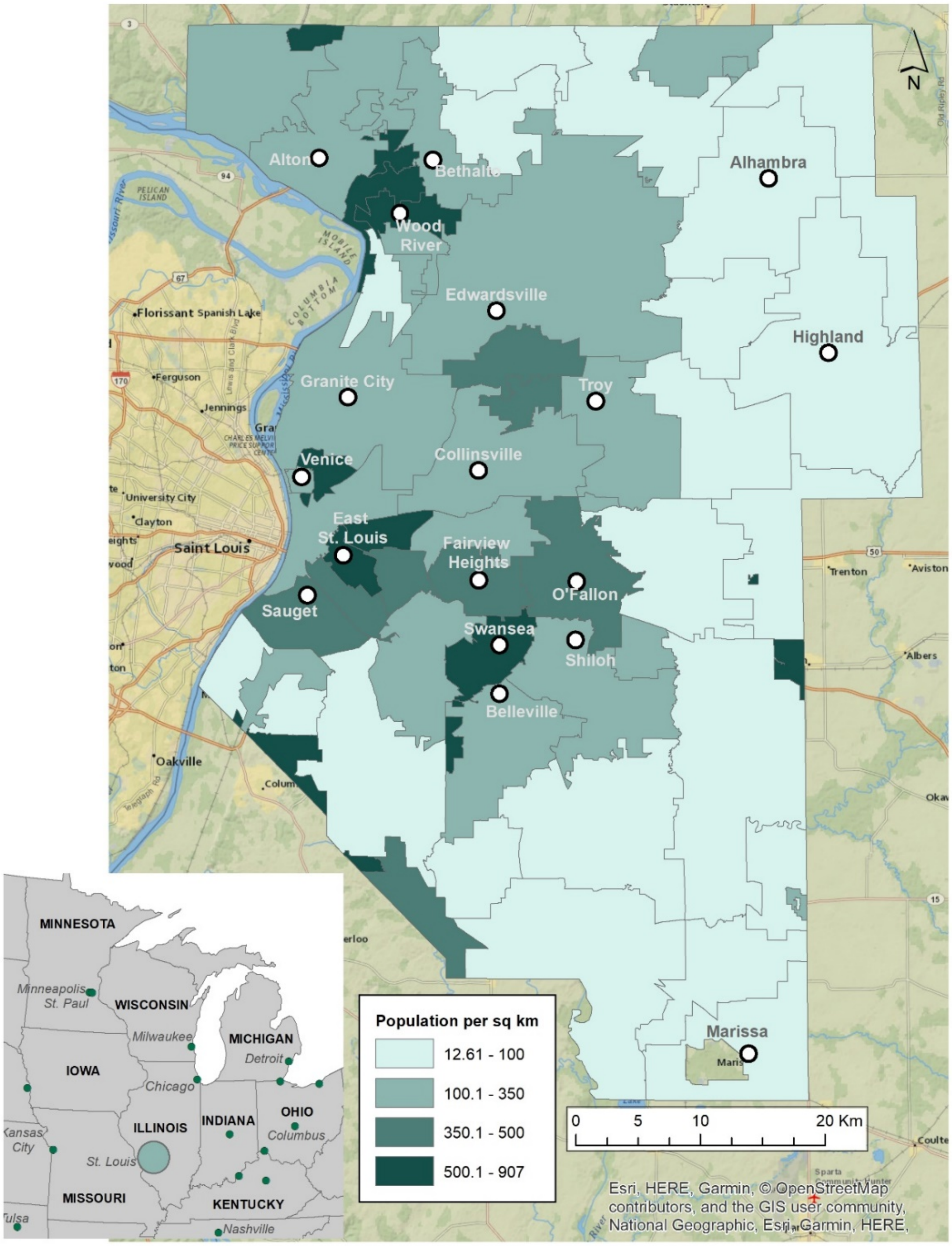

Figure 1. Study area with population density per square kilometer.

2.2.1 Respiratory Hospital Admissions

Respiratory hospitalizations were obtained through the Illinois Department of Public Health (IDPH) via an internal university grant. Records received included daily discharge records at the inpatient and emergency level by zip code of Illinois residents (IDPH 2013). Discharge records include a brief medical record regarding each patient discharged from an Illinois hospital. These records include a reason for utilizing the inpatient or emergency department such as diagnosis, admission date, cost, and unique hospital identifier as well as information related to the patient such as age, ZIP code of residence, race/ethnicity, and gender (Hare and Barcus 2007). The time frame is January 1, 2009 through December 31, 2011. In order to capture hospitalizations for respiratory diseases, specific diagnostic codes from the International Classification of Disease, Ninth Revision (ICD-9) ranging from 460-519 were analyzed. These codes represent a range of respiratory problems from acute respiratory infections such as tonsillitis and bronchitis, emphysema, pneumonia and influenza to chronic diseases such as asthma (ICD9Data). While working with the Illinois data, an apparent problem occurred with Illinois residents choosing to go to hospitals located in Missouri. There are two children's hospitals which are located in St. Louis, MO as well as higher level trauma centers. The residents that chose a Missouri hospital were not captured in the data from the IDPH. Therefore, additional respiratory discharge data was obtained from the Missouri Department of Health and Senior Services. This data was for the same ICD9 codes and time frame as mentioned above at the zip code level for Illinois residents using a Missouri hospital **(**MODHSS 2014**)**. If this data had not been acquired, roughly ten percent of hospitalizations would have been missing from this analysis. Therefore, it is vital to include discharge data from *both* states in this area. Three major respiratory problems caused residents to spend time in the hospital during 2009-2011: Pneumonia, Chronic Bronchitis, and Respiratory Failure. Emergency room visits consisted of these same three problems as well as more acute respiratory problems such as respiratory infections, asthma and influenza. As can be seen in Table 1, most of the respiratory disease visits are to the emergency room rather than needing to cause an overnight stay at the hospital.

Table 1. Hospitalization statistics.

Inpatient	**Madison**	**St. Clair**	**St. Louis, MO**	**Totals**
Pneumonia (486)	2,135	2,019	1,200	5,354
Obstructive chronic bronchitis with acute exacerbation (491.21)	1,334	1,142	423	2,899
Acute and chronic respiratory failure (518.81 and 518.84)	1,242	1,878	541	3,661
Emergency room	**Madison**	**St. Clair**	**St. Louis, MO**	**Totals**
Acute upper respiratory infections of unspecified site (465.9)	8,950	7,787	2,441	19,178
Acute pharyngitis (462)	6,932	8,104	730	15,766
Bronchitis (490) and chronic bronchitis (491.21)	7,107	5,682	379	13,168
Asthma (493.02,2,9,92)	4,630	6,057	1,350	12,037
Pneumonia (486)	2,651	2,888	619	6,158
Influenza (487)	1,348	1,876	550	3,774

2.2.2 Demographic Data

In order to understand if specific demographics are afflicted with respiratory hospitalizations and/or air pollution, demographic data was obtained from the US Census, American Community Survey 2007-2011 dataset at the zip code level (ZCTA). Variables of interest are percent White, percent African American, percent Hispanic, percent below poverty, median income, percent children (ages 5 and under), percent elderly (ages 65 and older), and percent of female headed households with children (U.S. Census 2011). Population density per square kilometer was calculated with total population from the ACS data. St. Clair County has slightly higher population and multiple areas with high population density, whereas with Madison County, there are fewer pockets of high population density, but these areas and most of the population are located on the western edge of the study area (Figure 1 and Table 2).

Table 2. Descriptive statistics.

Variables	St. Clair County	Madison County	Study Area ZIP
Pct. African American	30.2	7.97	17.5
Pct Hispanic	3.2	2.67	2.3
Pct Fem HH w/ kids	39.04	25.47	28.8
Pct HS only	31.1	26.4	34.7
Pct below poverty	16.3	13.3	15
Mean income	$63,837	$66,567	$62,545
Total population	270,259	268,459	550,051

Note: Study area ZIP includes both Madison and St. Clair Counties at the zip code level.

Figure 2 shows four demographic variables: under 5, over 65, percent African American and percent poverty. The age variables do not reveal a consistent pattern, although there are more dense pockets of elderly in the study area with one zip code having up to 34% of its resident over 65 compared to only 14% under five. Percent African American reveals higher concentrations in St. Clair County. Unfortunately, a visual correlation exists between residents in poverty and African Americans. Poverty seems to be more prevalent along the western border, close to the Mississippi River and decreases as you move eastward.

2.2.3 Air Pollution Sources

Specific pollution emission data will not be used in this study to determine air quality or pollution due to inactive air quality monitors throughout the study area during 2011. Therefore, proxy measures are used in the form of toxic facilities, roadways, and industrial land use parcels. The locations of toxic facilities come from the United States EPA TRI (U.S. EPA 2011). The data includes latitude and longitude to represent pollution source locations for the year 2011, types of chemicals released, and the release amount in pounds (U.S. EPA 2011). The most common chemicals released for the study area are Manganese, Zinc, Hydrochloric Acids and Nitrate compounds. This data was downloaded and displayed in ArcGIS 10.6.1 (ESRI).

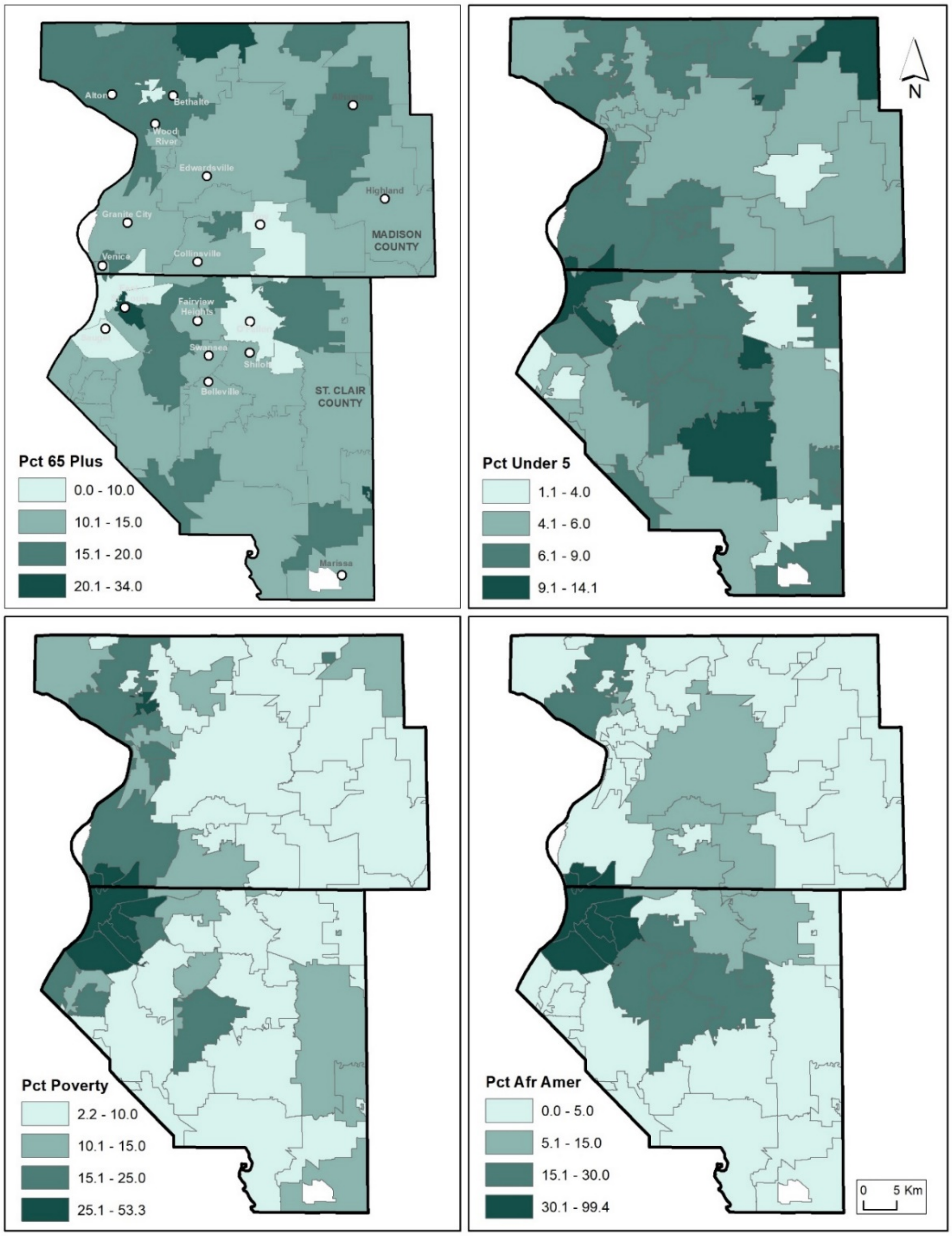

Figure 2. Spatial patterns of selected demographics.

An additional source of air pollution is vehicular and truck traffic. Data on the region's roadways were obtained from the East-West Gateway Council of Governments and consists of Interstates and Major Highways, as well as all residential streets. Rather than analyzing all possible vehicular and truck traffic routes, this study will only focus on major thoroughfares. This decision was made because truck traffic and commuter traffic contribute to the more significant sources of pollution (Maantay 2007) and living near these major thoroughfares have also been shown to increase chronic respiratory symptoms (Oosterlee et al. 1996). These roadways will be used as a proxy for nitrogen oxides, particulate matter, and volatile organic compounds. Finally, industrial land use was obtained from the Madison County and St. Clair County government offices as a shapefile showing areas that are zoned industrial for each county (as suggested in Mennis and Jordan 2005). When referring to air pollution, the substances under evaluation are those that constitute the pollutants from traffic and industrial-related sources that has been associated with significant adverse human health effects, specifically respiratory effects (Maantay 2007).

3 METHODS

There are "two methods of determining exposure potential to pollution: spatial coincidence method and proximity analysis" (Maantay 2007, 45). The spatial coincidence method takes any polluting facility that is within a county, tract, block group, etc. and links the pollution to all residents of that specific geography. For example, if a polluting facility was on the east side of a zip code, the entire zip code would be deemed a polluted zip code even though those residents on the west side of the zip code might not be impacted at all. In addition, if the polluting facility was in one zip code, but prevailing winds draw the pollution to the next zip code, the residents of the zip code without the facility would not be categorized as impacted by pollution. Pollution does not stay in one area or care about borders, so the spatial coincidence method could mask the true exposure to pollution for residents. The proximity analysis method analyzes each polluting facility based on specified distances. These distances are adjusted based on what types of facility are under investigation and their emissions. Rather than identifying the entire population, only those residents that fall within the designated distance or buffer are considered to be at-risk for the pollution. However, prevailing winds can also impact how far the pollutant travels and the designated distance used can also mask pollution risk.

Both methods have drawbacks in that one method assumes the risk is spread equally over a large geographic area and the proximity method assumes all those within the specified distance (usually buffer) are impacted equally. While the ideal option is to assess each pollution source and specific pollutant, this study will use the proximity analysis method along with additional GIS techniques to create a pollution density, similar to population density. "The buffers constructed were based on distances established as standards by environmental agencies or used most often by other researchers as the area of greatest potential impact from sources. TRI facilities had 805 meter buffers and roadways had a 150 m buffer" (Maantay 2007, 46-47). The industrial land use parcels also had an 805m buffer radius based on previous work related to the toxic facility research (Maantay 2007). These methods are not used to infer causality in the distribtuion of TRI facilties, but rather to explore the relationship between TRI facility locations, roadways, industrial land use, demographics and respiratory hospitalizations (Mennis and Jordan 2005, 254). By including these buffers, the analysis provides a good visualization, but additional work is needed to fully incorporate these pollution proxies for use in statistical analysis.

Once the buffers were created in GIS, three additional techniques were utilized to create a pollution density variable. First, each buffer was converted to a raster, then the extract by mask function was utilized, finally the tabulate field was used to create an area variable of how much pollution existed in each zip code. This new field was then divided by zip code area to create a density value. Road, TRI facility and industrial land use was analyzed separately to determine which pollution proxy contributed to the hospitalizations. Finally, each pollution proxy area was added together and divided by zip code area to create an overall pollution density value for each zip code.

Mapping the hospitalization, demographics, and pollution data is a good starting point to identify any potential commonalities, however, geostatistical techniques can help to identify the most influential variable. Incorporating a spatial component to address dependency is vital for this type of geographic research (Chakraborty 2009; Jephcote and Chen 2012; Mennis and Jordan 2005). To see the differences between accounting for spatial dependency, Pearson's correlations were performed as well as local indicators of spatial autocorrelation (LISA). More detailed reviews of the importance of spatial autocorrelation and spatial dependence can be found in Chakraborty 2009, Gilbert and Chakraborty 2011, Grineski and Collins 2008, and Pastor et al. 2005. Due to the influence of spatial autocorrelation, ordinary least squares regression is not an acceptable technique to use in this analysis. In addition, reviewing the descriptive statistics with the hospitalization data reveals that the variance is quite large when compared to the mean, therefore, negative binomial regression will be used to account for this overdispersion (Hilbe 2011, Sauber-Schatz et al. 2013, Ardilles et al. 2018). All analyses were performed using Geoda and SPSS.

4 RESULTS

4.1 Respiratory Hospitalizations

For the years 2009-2011, Metro East residents recorded 129,088 visits for respiratory hospitalizations falling under the ICD codes of 460-519; this represents 13.5% of visits to hospitals. Since the data is aggregated by zip code, this does not exclude multiple visits for the same individual(s). The majority of the visits, 83.5% were to the emergency room, whereas only 16.5% were admitted at the inpatient level. The primary reason for being admitted to the hospital was pneumonia and the primary reasons for going to the emergency room were for acute respiratory infections and acute pharyngitis (Table 1). Figure 3 displays the spatial distribution of hospitalizations for residents in the Metro East. The zip code with the highest hospitalization rate is 62059, with a zip code population of 459, which is just south of the city of Venice. Farther to the east, the small zip code of 62289, with a zip code population of 370, which is to the east of O'Fallon had the next highest rate of hospitalizations. The next four highest hospitalization rates are in the East St. Louis and Sauget area. While the top two zip codes for hospitalization may be due to small population numbers, the other zip codes with high hospitalization rates correspond to high areas of air pollution with multiple TRI facilities, roadways, and industrial parcels located in these zip codes.

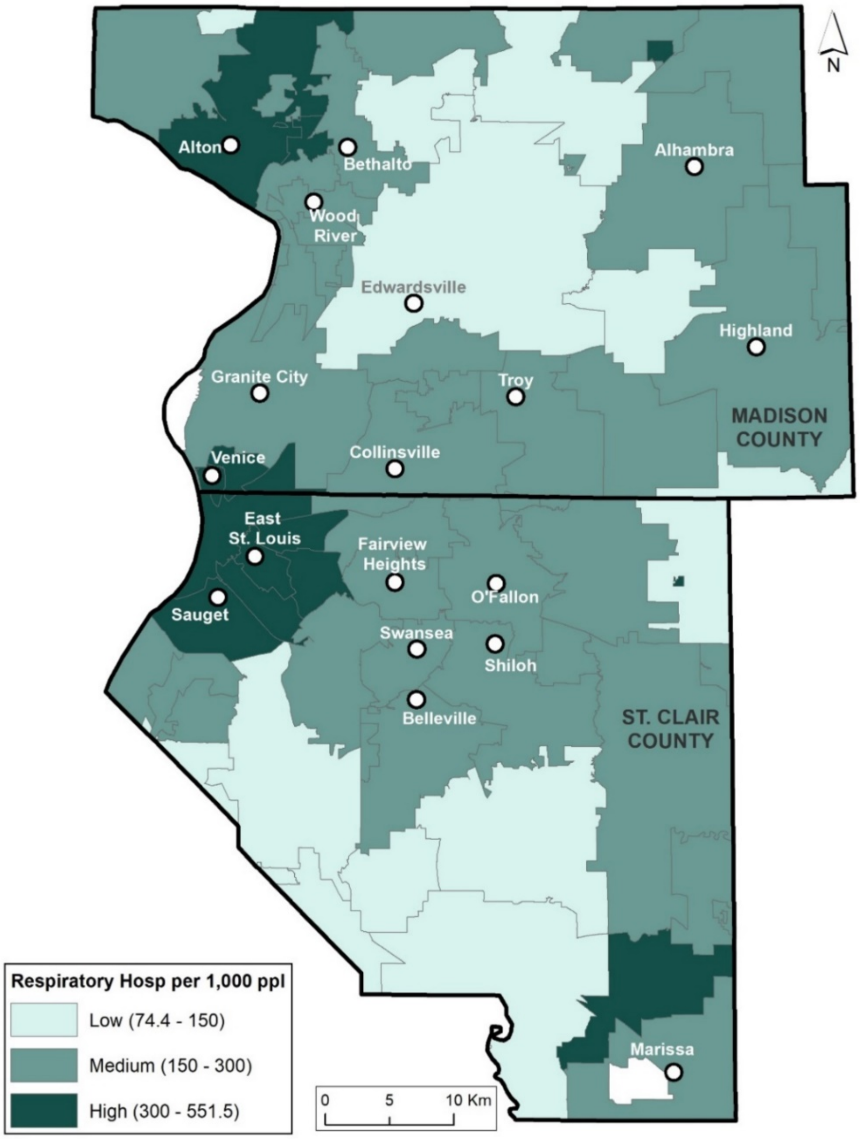

Figure 3. Hospitalization rates due to respiratory disease codes, 2009-2011.

4.2 Pollution Sources

A geographical pattern exists when looking at the pollution sources for the Metro East (Figure 4). There is a total of 55 TRI facilities in the Metro East. In both counties, the TRI facilities become extremely limited or nonexistent as you move farther to the east. In fact, 75% of the toxic facilities are located along the western edge of the study area. This pattern makes sense as the facilities are located near multiple break-in-bulk points. Facilities could utilize the river for transportation or one of the many interstates, or even local airports. The toxic facilities are similarly located as the respiratory hospitalizations. Using the spatial join feature in ArcGIS, the number of TRI facilities per zip code was calculated. The zip code with the highest number of facilities is in the Granite City area with 11 facilities in one zip code. This zip code is located near many options for transportation and is home to a steel mill and other industrial facilities. The industrial land use parcels follow a similar west-to-east pattern and the majority of parcels include TRI facilities. However, there are many industrial land use parcels that do not have a TRI facility, which gives an indication of potential pollution exposure. Major roadways exist throughout the study area with many converging in the East St. Louis area in order to cross the Mississippi River. There are six bridges that connect the two counties to the MSA, three bridges alone in East St. Louis that cause large amounts of traffic to converge at certain points along with pollution.

Many studies analyzing pollution utilize the proximity analysis method of constructing buffers around specific pollution sources (Abel 2008; Grineski and Collins 2008; Maantay 2007). In this study, 805-meter buffers were drawn around the TRI facilities and the industrial land use parcels and a 150-meter buffer was drawn around the major roadways. Each of these buffers created a separate layer in ArcGIS that was then merged together to create a map of pollution exposure for the Metro East (Figure 5). Approximately 37% of the Metro East's land mass falls within the combined buffers (Maantay 2007). However, this is heavily skewed near the west side of the study area. One layer that is not skewed towards the west are the industrial land use buffers. While these land use parcels might not be easy to see in Figure 4, including a buffer reveals that most cities have designated some land to industrial production. Therefore, only including TRI facilities in pollution research is masking a potential larger threat of industrial land use parcels. A limitation is that these are only *designated* places for production, not proof of actual industrial activity.

These proximity buffers can be superimposed on the respiratory hospitalizations to reveal a visual correlation (Figure 6). There seems to be a pattern of potential pollution and high respiratory hospitalizations, which take place on the western edge of the study area. This area also corresponds to high rates of poverty, children, and African Americans (Figure 2). The areas surrounding East St. Louis and Sauget as well as Granite City seem to have the highest rates of potential pollution and respiratory hospitalizations and poverty, an area with a potential *triple threat*.

Providing a visual correlation is a starting point, but additional GIS analysis was performed to turn those buffers into a density measurement. As mentioned in the Methodology, multiple steps were performed to create a road density, TRI density, industrial land use density, and an overall pollution density value. These values represent the area of buffer that exist in each zip code. Figure 7 provides the maps that showcase the new pollution density variable.

4.3 Geostatistical Results

A visual relationship is revealed when mapping respiratory hospitalizations, demographics, and pollution sources in the Metro East (Figure 6). However, more robust analysis is needed for statistical relationships. First, a Pearson correlation matrix was calculated with the respiratory hospitalization rates and various demographic and density data (Table 3). Upon first look, the results seem promising in that many variables are highly correlated with respiratory hospitalizations. However, multi-collinearity existed amongst many variables. In addition, LISA reveal that there is spatial autocorrelation present in the data and therefore, these Pearson correlation coefficients might be revealing spurious relationships.

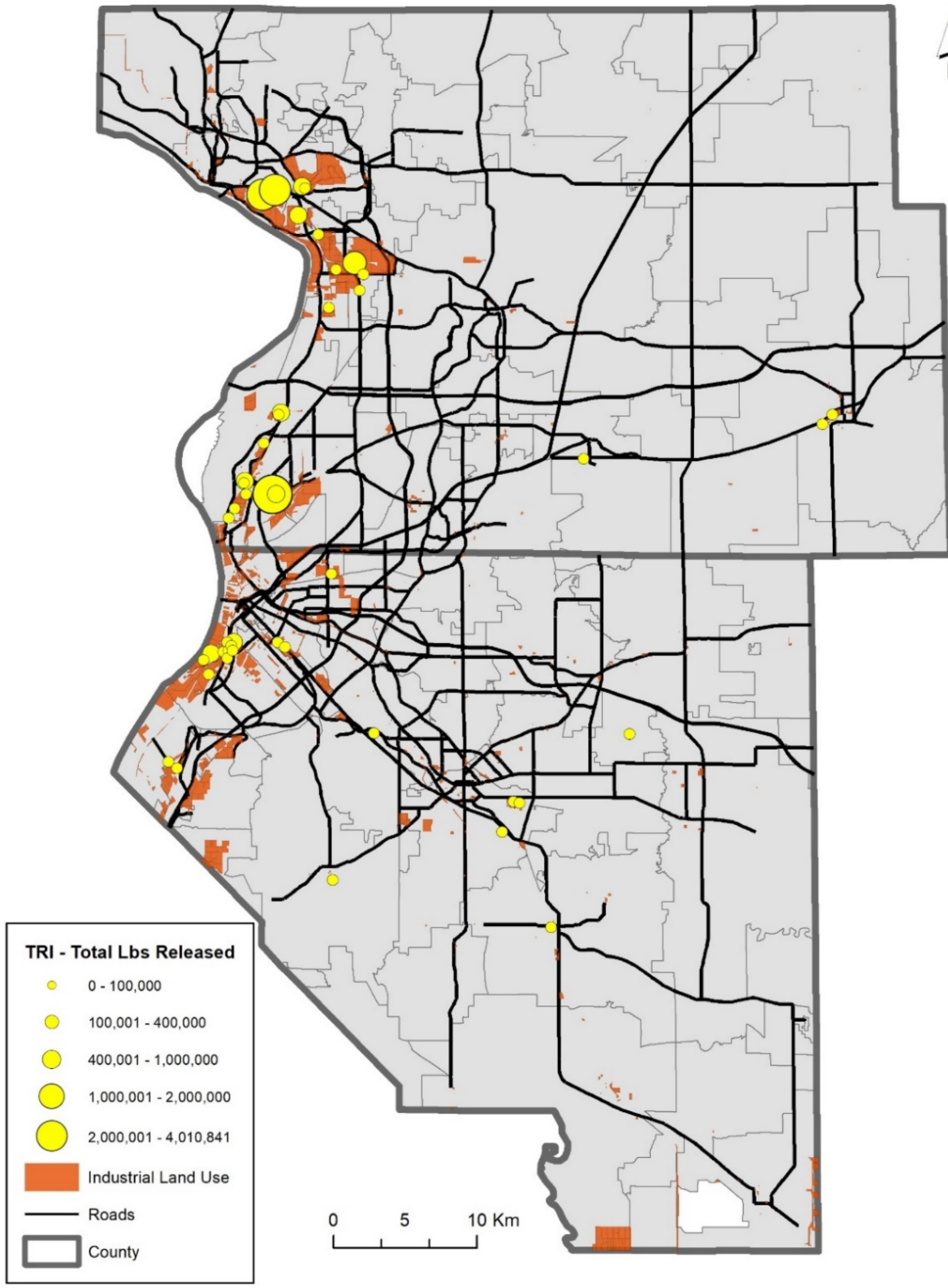

Figure 4. Pollution sources of toxic facilities, industrial land use parcels and major roadways.

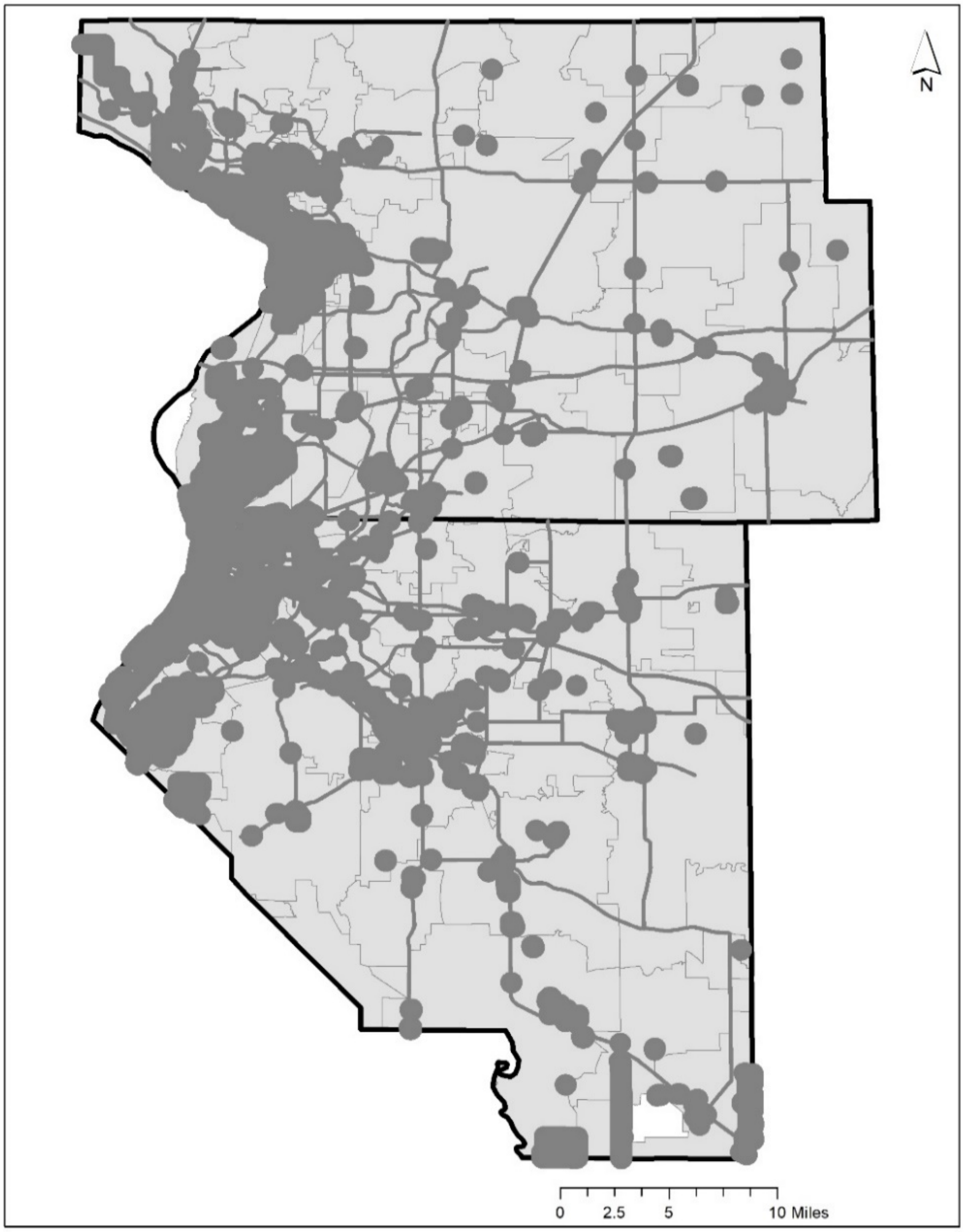

Figure 5. Pollution density for the study area created by using 805 meter buffers around TRI facilities and industrial land use parcels and a 150 meter buffer around roadways (37% of study area falls within the combined buffers).

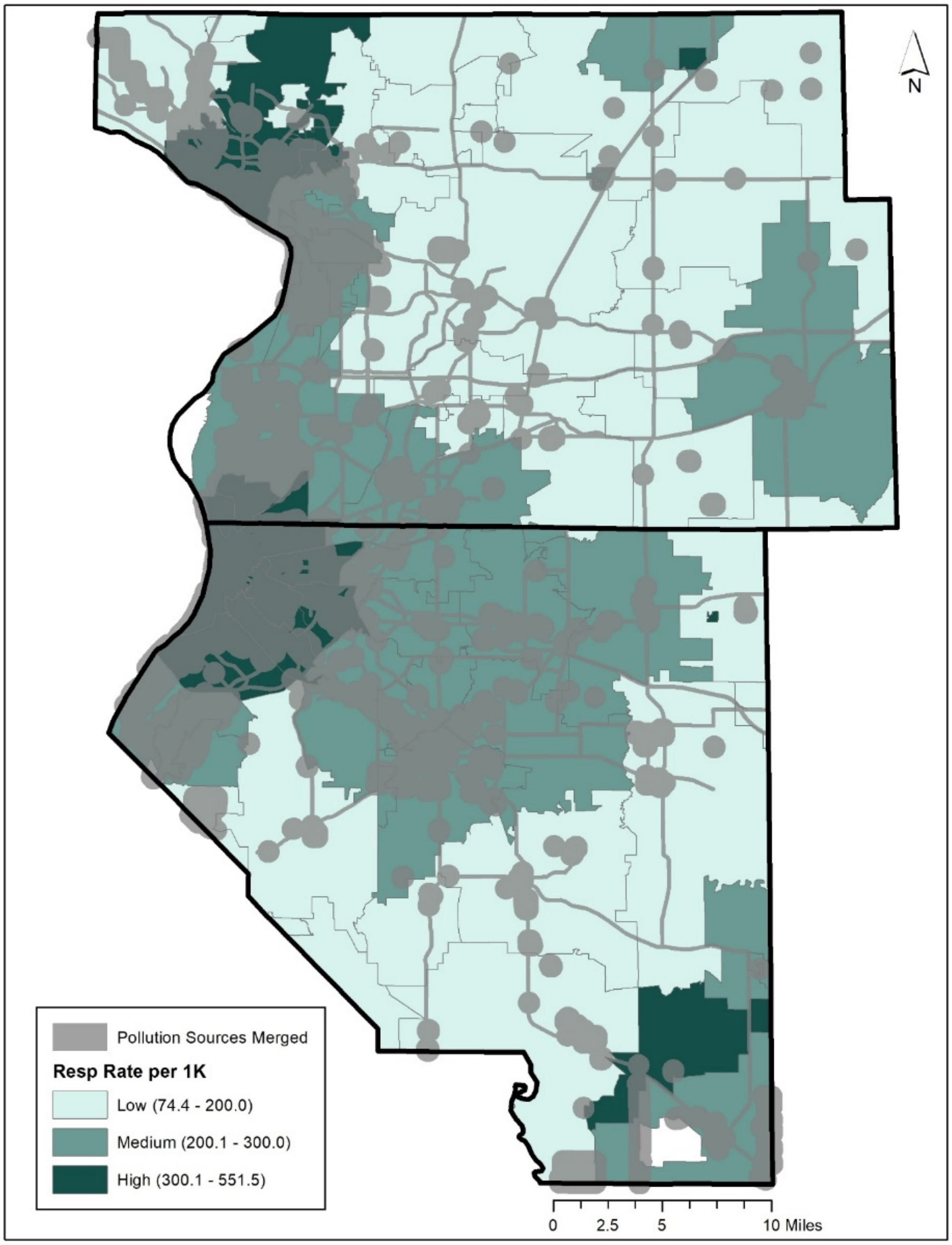

Figure 6. Combined map of respiratory hospitalizations and buffered pollution sources.

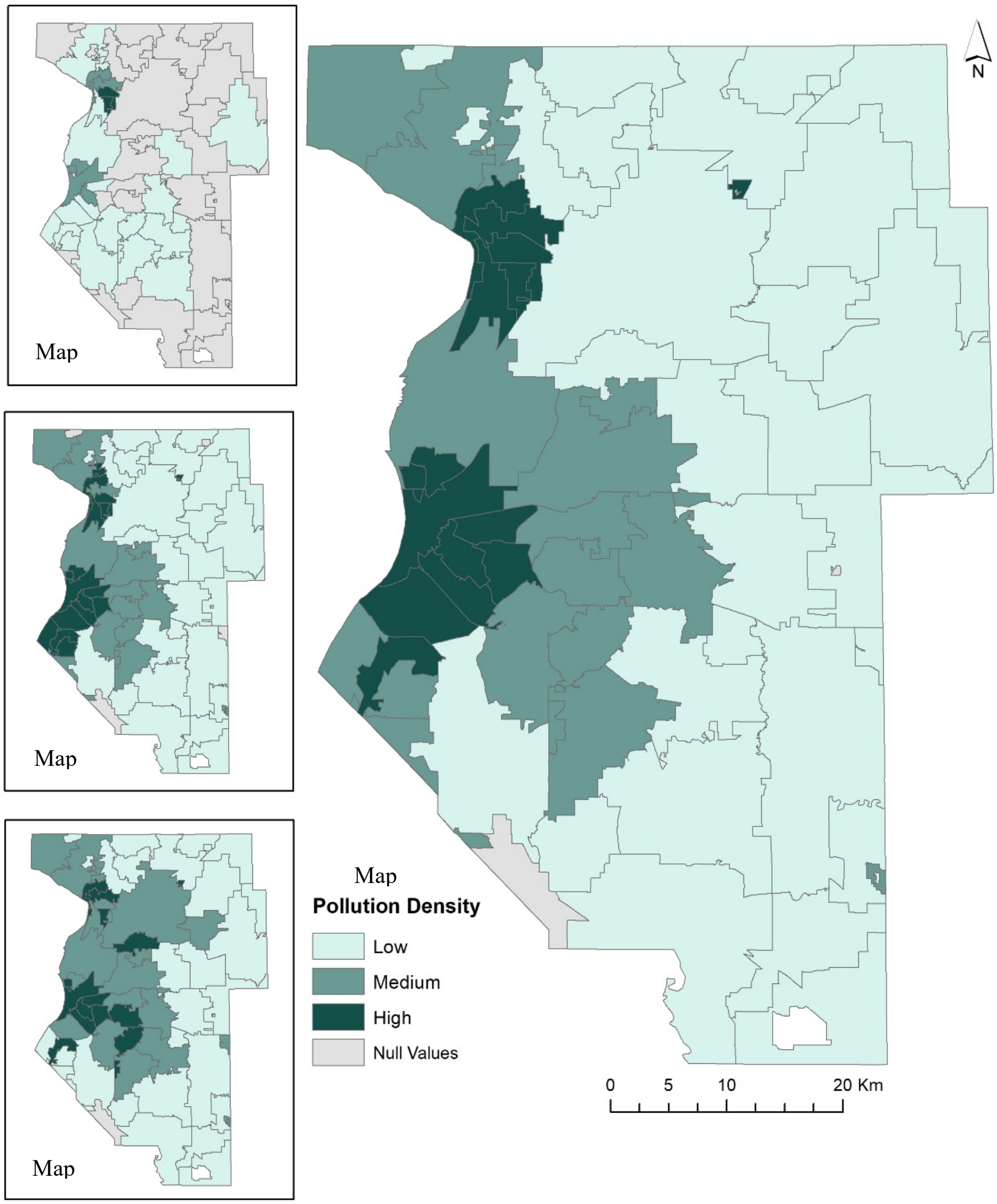

Figure 7. Densities of various pollutants (A-TRI, B-industrial land use, C-roads, D-combined).

In order to account for the multi-collinearity and spatial autocorrelation, two additional procedures were utilized: bivariate Local Moran's *I* and negative binomial regression. The only variable that becomes significant for respiratory hospitalization is percent poverty. Figure 8 reveals bivariate Local Moran's *I* significance maps for respiratory hospitalization and poverty (Local Moran's *I* of 0.553) (Anselin et al. 2010). The various pollution densities have a 0.088 Local Moran's *I* value compared to respiratory hospitalizations. Even though the pollution density is not statistically significant with respiratory hospitalizations, there are hot spots of clustering in the East St. Louis region along the western edge of the study area. These results reveal that pollution sources are not the main reason for respiratory hospitalizations.

Table 3. Pearson correlations of total respiratory hospitalizations.

Variables	**Corr.**	**Sig.**
Percent Afr. Amer.	0.736	0.000
Under 5	0.188	0.147
Percent no HS diploma	0.685	0.000
Percent below poverty	0.790	0.000
Population density	–0.441	0.000
TRI density	0.352	0.005
Industrial parcel density	0.661	0.000
Road density	0.567	0.000

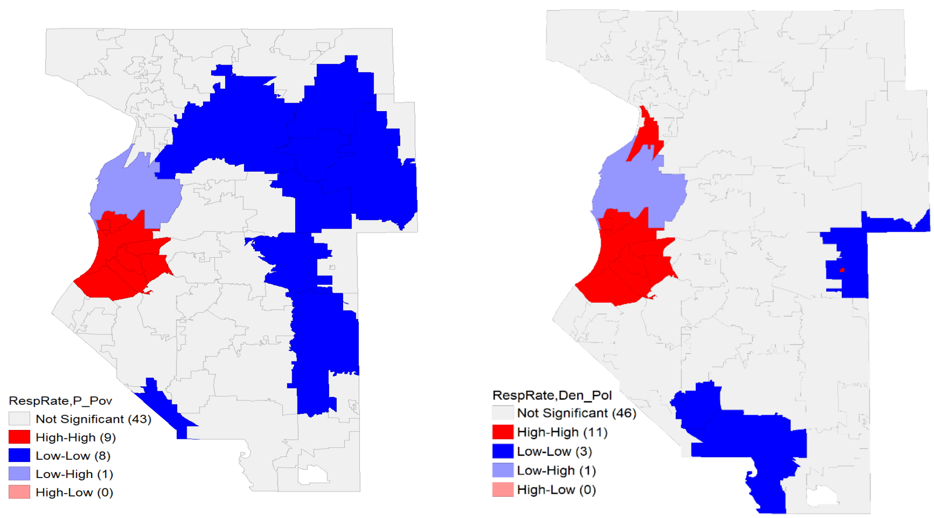

Figure 8. Bivariate local Moran's *I* cluster maps of respiratory hospitalizations and poverty (left) and respiratory hospitalizations and pollution density (right).

The results of the negative binomial regression are similar to those shown with the Moran's *I* analysis. The only significant variable for the negative binomial regression model was poverty, therefore, poverty has the largest impact on respiratory hospitalizations (RR=1.02; 95% CI = 1.017-1.028). The incident rate ratio can be interpreted as for every one unit increase of respiratory hospitalizations, there was an average 2.2% increase in poverty for the zip code. Interpreted in another way, the chances of going to the hospital for respiratory problems increases 2% if you live in a high poverty zip code.

5 DISCUSSION AND CONCLUSION

This paper has shown that a potential "triple threat" is *not* occurring throughout the Metro East of St. Louis, MO-IL. By analyzing health, demographics and pollution, this research has shown that poverty is more influential for this area than any other variable.

Disentangling the poverty component could reveal this area to have a lack of insurance or a lack of doctors, which would lead to utilizing the hospital as a primary care physician. Expanding hours of availability, Medicare and Medicaid, or educational materials about various respiratory diseases could aid in reducing the need for hospitalizations for the residents along the western edge of the study area.

There does seem to be a *double burden* that exists for the western edge of the study area, with high rates of poverty and respiratory hospitalizations as well as areas with high pollution exposure (Figure 8). However, unlike previous studies analyzing environmental justice issues and health, the minority component is not significant in the Metro East. While a Pearson correlation revealed significant relationships between African American residents and respiratory hospitalizations, the bivariate Local Moran's *I* did not confirm this relationship. Another important factor is the use of these spatial statistics to account for autocorrelation and the negative binomial regression in order to account for overdispersion.

This article addressed multiple gaps in the literature regarding environmental justice. It utilized both mobile and stationary sources of pollution by including TRI facilities and roadways. It also added industrial land use parcels as well as using geostatistical techniques such as Bivariate Local Moran's *I* cluster analysis and negative binomial regression. Respiratory hospitalization data for 2009-2011 was used to identify any clustering with pollution sources as well as demographics.

Like all spatial studies exploring the impact of air pollution on health, this study has limitations. The use of the zip code for unit of analysis is difficult to truly identify where in the zip code the most hospitalizations occur. The ZCTA in some areas is quite large and in others it is quite small. This can lead to inconsistences and complications in generalizing findings. However, hospital discharge data does reveal when and why people utilize the hospital, which is important for medical and health geography as well as identifying areas to study in greater detail. Additionally, using hospitalizations does not capture those residents that are controlling their respiratory disease with medication or regular doctor visits. This discharge data only reveals the worst-case scenarios for respiratory diseases or some trigger that made the resident go to the hospital. Therefore, the true picture of respiratory disease is incomplete for this area due to only using discharge data. Additionally, discharge data does not have a patient id so some of the records could refer to multiple hospitalizations for one patient. Despite these limitations, this research has produced results that are similar with other environmental justice and health studies, especially others that have analyzed the St. Louis MSA (Abel 2008, Sarnat et al. 2015; Winquist et al. 2012).

In addition, the use of proxy measures for pollution is not the ideal situation. Future research will try to analyze specific pollutant types, if and when they become available, that contribute to respiratory problems such as ozone, nitrous oxide and particulate matter. Additional methodology procedures such as using dispersion models or creating riskscapes could enhance the impact of pollution on respiratory health for the region. Incorporating other diseases such as cardiovascular diseases (strokes) could also reveal that demographics, specifically poverty, in St. Louis is impacting more than just the lungs of the residents.

In conclusion, this study found no *triple threat* for residents in the Metro East regarding pollution, respiratory hospitalizations and demographics. There was a strong *double burden* with poverty and respiratory hospitalizations. The risk burden for respiratory hospitalizations increase for residents living in poverty. The research presented here could assist local advocacy groups, health departments, and low-income residents in the Metro East to encourage additional examination and oversight to get more people out of poverty, give more people cleaner air as well as better health for all.

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